Improving Recommendation Ranking by Learning Personal Feature Weights*

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Abstract. The ranking of offers is an issue in e-commerce that has received a lot of attention in Case-Based Reasoning research. In the absence of a sales assistant, it is important to provide a facility that will bring suitable products and services to the attention of the customer. In this paper we present such a facility that is part of a Personal Travel Assistant (PTA) for booking flights online. The PTA returns a large number of offers (24 on average) and it is important to rank them to bring the most suitable to the fore. This ranking is done based on similarity to previously accepted offers. It is a characteristic of this domain that the case-base of accepted offers will be small, so the learning of appropriate feature weights is a particular challenge. We describe a process for learning personalised feature weights and present an evaluation that shows its effectiveness.

1 Introduction

A particular challenge for e-commerce is to provide mechanisms that substitute for the ways in which the human sales assistant facilitates the sales process. An important component of this is the ability to identify the customer’s preferences and highlight products and services that will satisfy the customer’s requirements and preferences. This is particularly true in the travel domain. A dialog with a good old-fashioned business travel agent would contain phrases like; “I presume you will want to go out on the first flight.”, “You will want to return on the Friday evening.”, “You will not want a stopover in Heathrow.” Ideally, an online Personal Travel Assistant will learn these preferences as well.

In this paper we describe such a system that uses CBR to rank offers returned in response to a travel request [6]. There are two types of cases in this system; session-cases and offer-cases. Session-cases represent previous user-interactions or sessions with the system and offer-cases represent individual travel offers. Session-cases can be viewed as request-offer pairs; the problem component of the case is made up of a previous travel request with some additional contextual information; the solution com-

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ponent is a reference to the selected offer (which is an offer-case) in response to that request. The idea behind this is that a user’s preferences are encoded implicitly in the accepted offers to particular requests and that similar requests will lead to similar selections of offers. So the ranking is a two-stage process. The first stage is to find a previous session that contains a similar request to the current travel request. This session is assumed to be relevant to the user’s current context. In the second stage, the current offers are ranked based on their similarity to the offer component of the retrieved session-case. This session-based recommendation approach is analogous to that used in Ricci et al.’s DieToRecs system [10]. Both systems rank presented items based on their similarity to items selected in response to similar queries in the past (twofold similarity) [11]. However, DieToRecs differs from our system in that it uses a mixed-initiative approach to elicit user preferences whereas we determine these preferences implicitly. We incorporate these preferences into the similarity measures used in the recommendation process. Some users will be very price conscious, others will be adverse to stopovers or long stopover times, and others will have preferences on departure times. Rather than ask users to weight the importance of these criteria we choose to learn this from past behaviour. There are two reasons for this, first, it places less cognitive load on the user. Second, it avoids the problem of asking users to assign numeric weights to criteria – a skill at which people are notoriously poor.

We use techniques along the lines of introspective learning as described in the past by Bonzano et al. [2], Branting [4] and Stahl [13, 14]. Introspective learning refers to an approach to learning problem solving knowledge by monitoring the run-time progress of a particular problem solver. The approach used here is failure-driven in the sense that an attempt is made to improve feature weights only in the case of a recommendation failure. This is done by decreasing the weights of unmatching features and increasing the weights of matching features. This will tend to push down the recommendation scores of offers that are not being taken up and pull up the scores of ones that are selected.

Section 2 discusses a number of feature weighting algorithms where user feedback drives learning. Section 3 describes our Personal Travel Assistant application and how CBR is used to recommend flights to users. In Section 4 we give a description of our feature weight learning algorithm. Section 5 presents results that show that weight learning improves recommendation accuracy. We discuss some future work in Section 6 and draw our conclusions in Section 7.

2 Feature Weighting Based on User Feedback

There are a number of systems that use user feedback to assist in problem solving episodes. Mixed initiative CBR and conversational CBR systems use feedback to direct a search through a problem space, e.g. [5, 9, 12, 11]. Some learners attempt to incorporate a level of utility [1] into the similarity measures by looking at case order feedback [2, 4, 13, 14]. Utility is indicative of adaptability or usefulness to the current problem. We hope that by incorporating utility into the similarity measure in this way we will improve and personalise recommendations in our system.